Deutsches Institut für
Wirtschaftsforschung

DIW BERLIN

Discussion Papers

1023

Amil Dasgupta • Roberto Leon-Gonzalez • Anja Shortland

Regionality Revisited: An Examination of the Direction of Spread of Currency Crisis

Berlin, June 2010

IMPRESSUM

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin
Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
http://www.diw.de

ISSN print edition 1433-0210
ISSN electronic edition 1619-4535

Available for free downloading from the DIW Berlin website.

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN.
Papers can be downloaded free of charge from the following websites:

http://www.diw.de/de/diw_01.c.100406.de/publikationen_veranstaltungen/publikationen/diskussionspapiere/diskussionspapiere.html
http://ideas.repec.org/s/diw/diwwpp.html
http://papers.ssrn.com/sol3/JELJOUR_Results.cfm?form_name=journalbrowse&journal_id=1079991

Regionality Revisited: An Examination of the Direction of Spread of Currency Crises

Amil Dasgupta, Roberto Leon-Gonzalez, and Anja Shortland

This draft: March 2010

Addresses for correspondence: Dasgupta (corresponding author) Department of Finance, London School of Economics, London, WC2A 2AE, UK. E-mail: a.dasgupta@lse.ac.uk
Leon-Gonzalez: National Graduate Institute for Policy Studies, Tokyo and Shortland: Department of Economics, Brunel University and DIW Berlin

Acknowledgements: We thank the co-editor, Michael Melvin, and an anonymous referee for helpful comments. We are also grateful to Hugo Benitez-Silva, Giancarlo Corsetti, Emilio Gómez-Déniz, Fernando Fernández-Rodríguez, Andrew Patton, Jorge Pérez-Rodríguez, John Rust, and Francisco J. Vázquez-Polo for helpful comments, and to Beatrice Weder for sharing the data on the 1998 crisis. Dasgupta thanks the ESRC for financial support. Leon-Gonzalez thanks the financial support of the Japan Society for the Promotion of Science (start-up grant, #20830025).

Abstract

What determines the direction of spread of currency crises? We examine data on waves of currency crises in 1992, 1994, 1997, and 1998 to evaluate several hypotheses on the determinants of contagion. We simultaneously consider trade competition, financial links, and institutional similarity to the "ground-zero" country as potential drivers of contagion. To overcome data limitations and account for model uncertainty, we utilize Bayesian methodologies hitherto unused in the empirical literature on contagion. In particular, we use the Bayesian averaging of binary models which allows us to take into account the uncertainty regarding the appropriate set of regressors.

We find that institutional similarity to the ground-zero country plays an important role in determining the direction of contagion in all the emerging market currency crises in our dataset. We thus provide persuasive evidence in favour of the "wake up call" hypothesis for financial contagion. Trade and financial links may also play a role in determining the direction of contagion, but their importance varies amongst the crisis periods.

JEL Classification: F31, F32, C11

Keywords: Financial contagion; Exchange rate; Institutions; Bayesian Model Averaging

1 Introduction

Currency crises tend to occur in waves. In repeated instances from the early 1970s to the late 1990s it has been observed that when speculative attacks lead to a currency crisis in one country, market volatility tends to spread to other countries in the region and elsewhere. Several mechanisms have been proposed to explain this phenomenon, generally referred to as contagion. Commonly discussed mechanisms include the transmission of crises through trade and financial links between countries, as well as the (rational) updating of beliefs by financial traders about the sustainability of specific institutional and developmental models. The latter is sometimes referred to as the "wake-up call" theory of financial contagion.

In this paper we empirically evaluate the relative importance of a number of potential transmission mechanisms that have been proposed in the existing literature, by analysing four waves of currency crises in the 1990s. We make two contributions.

First, we simultaneously include institutional (quality-of-governance) variables alongside the trade, finance and macroeconomic variables commonly analysed in empirical literature on contagious currency crises, thereby directly testing the "wake-up call" hypothesis.

Second, we utilize Bayesian methodologies hitherto unused in the empirical literature on contagion to overcome model uncertainty and data limitations. In particular, we use Bayesian averaging of binary models, which allows us to take into account the uncertainty regarding the set of regressors that should be included in the empirical analysis of contagion.

Before proceeding further, it is worth clarifying the remit of our exercise. In this paper we do not seek to enter the debate on whether contagion exists. While there are now several theoretical equilibrium models of contagion, there is not yet complete empirical agreement about whether contagion exists.[1] In this paper, we simply *assume* that contagion exists and aim only to shed light on the mechanisms by which it may propagate.

Much of the extant empirical literature on contagious currency crises stresses the phenomenon of regional contagion. It focuses on trade and financial links, which tend to occur in geographical clusters, and finds evidence in favor of both as potential transmission mechanisms for contagion.[2] However, the currency crises of the 1990s have spread far beyond the region of

[1] See Dungey and Tambakis (2003) for a discussion of the term "contagion" as well as Dungey *et al* (2003) for a detailed review of the contagion literature.

[2] Eichengreen *et* al (1996), Glick and Rose (1999), Kaminsky and Reinhart (2000), Caramazza et al (2000), Van Rijckeghem and Weder (2003).

the original crisis country. Glick and Rose (1999) deem that Hong Kong, Indonesia, the Philippines and Thailand were affected by the "Mexican crisis" in 1994/1995, while Argentina, Brazil, the Czech Republic, Hungary and South Africa are considered to have been among the victims of the Asian Crisis. According to Van Rijckeghem and Weder (2001) the Russian crisis of 1998 affected 16 countries outside the former Soviet Union, including Argentina, Hong Kong, Indonesia, South Africa and Turkey. While trade competition in third markets or financial links may be possible explanations for extra-regional contagion, it is also interesting to examine the possibility that a speculative attack on a country follows from a "wake-up call" regarding a specific model of development: a currency crisis in one country may highlight vulnerabilities associated with a particular set of institutional features, which may also be found in other countries outside the region.

There is now much data measuring the institutional features of different countries. Our paper contributes to the literature by directly testing the extent to which institutional similarity with the "ground zero" country determines the direction of spread of currency crises. This is done while simultaneously considering standard factors such as trade competition and financial links to give an overall view of the drivers of financial contagion in foreign exchange markets.

In addition, our paper utilizes recent econometric methodology that is relevant to the empirical analysis of financial contagion. There is no universally agreed-upon theoretical model of contagion: several alternative hypotheses coexist. In the presence of such model uncertainty, Bayesian model averaging (BMA) is a natural candidate for empirical work in this area. The idea of BMA was first proposed by Leamer (1978). It is a tool for forecasting and estimation when the researcher does not know the true model. Starting from a prior where all possible models are considered to be equally good, the method allows researchers to estimate the posterior probabilities of the models, using the data, and then weight their estimates and forecasts from each model by such posterior probabilities. While BMA has recently been extensively used in applied problems (see various references below), we are the first to use it in the context of financial contagion.

In addition to this, Bayesian methods allow us to overcome data limitations. Empirical samples in the contagion literature are of necessity small: in all previous studies the number of observations is below 100 countries. Of these only a small subset experience a crisis in each episode of contagion. Unlike maximum likelihood, Bayesian methods are also valid in small samples.

Summary of Results

We examine data on currency crises in 1992, 1994, 1997, and 1998, focusing on the relative importance of trade, financial links, and institutional similarity on the direction of contagion. We report the following results:

1. Institutional (quality-of-governance) variables play a vital role in the spread of all emerging market currency crises in our dataset. Following a crisis in the "ground zero" country, countries that are, ceteris paribus, institutionally similar have a higher probability of experiencing a currency crisis. In the crises of 1994, 1997, and 1998, the increase in crisis probabilities due to institutional similarity ranges between 11% and 40%. Our results, therefore, provide substantial empirical support for the "wake-up call" hypothesis for financial contagion.
2. Other factors, such as financial links (through common lenders) and trade also play a role in determining the direction of contagion, but their importance may vary across crisis periods. For example, financial links appear to be important in the 1998 crisis, while trade competition is important for 1994 and 1997.
3. The 1992 EMU crisis is significantly different from the emerging market crises, probably reflecting that it was about the sustainability of a system of exchange rates rather than the maintenance of unilateral pegs.

Our paper is linked to a large and growing literature on financial contagion. In what follows, we briefly survey this literature.

2 Literature review

The literature has considered a number of potential channels for international financial contagion.[3] The first potential channel derives from international trade.[4] If a country experiences a sharp devaluation it gains a competitive advantage over its trade partners and over competitors

[3] See Pericoli and Sbracia (2003) and Dungey *et al* (2003) for literature reviews.
[4] For a theoretical formalization of this idea see, for example, Gerlach and Smets (1995).

in third markets. To the extent that (the expectation of) deteriorating current account deficits signals potential currency weakness, countries with strong trade connections to the "ground zero country" become more likely to experience a speculative attack. Glick and Rose (1999) examine the importance of the trade channel and find statistical evidence from cross-country data that currency crises spread among countries which have strong trade links.

A second potential channel of contagion derives from financial linkages between countries.[5] Here contagion arises because groups of countries rely on common creditors and investors. If a country experiences a speculative attack, its major creditor banks may experience liquidity problems, which undermine their ability to provide emergency finance to other countries or trigger capital outflows to restore capital adequacy ratios. Therefore, countries which rely on external funding from the same creditors and investors as the "ground zero country" become vulnerable to speculative attacks. The importance of the "common creditor effect", meaning contagion through bank lending, has been empirically examined by Van Rijckeghem and Weder (2001 and 2003), Caramazza *et al*. (2000), Hernandez and Valdes (2001) and Kaminsky and Reinhart (2000). The results indicate that vulnerability to speculative attacks can spread among clusters of countries which depend on the same lenders. Caramazza *et al*. (2000) additionally show that countries which are more important to the common lenders are more likely to become crises countries than those which only receive a very small proportion of the common lenders' total lending.

A third channel for contagion derives from shared updating by market participants about the sustainability of specific institutional frameworks or development models. Such a view of contagion is commonly referred to as the "wake-up call" hypothesis.[6] The argument here is that if a country with a particular development strategy, institutional set-up or macroeconomic situation experiences a devaluation, this may be seen as revealing information about the vulnerability of countries of a similar "type" and hence cause the spread of crises.[7] A good example of a major re-evaluation of an economic development strategy was seen in the rapid

[5] For theoretical models formalizing this hypothesis, see, for example, Goldstein and Pauzner (2005), Allen and Gale (2000), and Dasgupta (2004).
[6] The term "wake-up call" originates from Goldstein (1998). For theoretical formalizations of this hypothesis, see Rigobon (1998) and Basu (1998). Van Rijckeghem and Weder (2003) provide evidence for the "wake-up call" hypothesis from the Russian crisis, which caused generalized outflows from emerging markets.
[7] See Drazen (1998) on "information externalities"

turn-around in 1997 from applauding the "Asian Miracle"[8] to deploring the "Asian Debacle". Months before the crisis South East Asia's "dedicated capitalism"[9] and "Asian values" were praised and held up as strategies for successful development the world over, but were swiftly condemned as "crony capitalism" in the immediate aftermath of the crisis and held responsible for economic vulnerabilities. Issues such as "corruption", "regulatory quality" and "transparency" suddenly came to the forefront of investor attention and may have contributed to the spreading of the crisis to countries perceived to have similar deficits in accountability and data quality. While a large literature has emerged in recent years to measure and quantify the effects of legal and institutional variables on financial development[10] and financial fragility[11] to our knowledge no direct test of the impact of institutional similarity on financial contagion has been carried out. It is a contribution of this paper to provide a direct examination of the "wake-up call" hypothesis using measures of institutional similarity provided in the literature.

3 Data

In Table 1 we summarize the variables that we use. For a given wave of currency crises and for each country *i*, the dependent (binary) variable records whether country *i* experienced a currency crisis following the crisis in the ground zero country. The information is taken from Glick and Rose (1999) for 1992, 1994 and 1997 and from Van Rijckeghem and Weder (2001) for 1998. [12] Glick and Rose (1999) identify Finland as the ground zero country for 1992, Mexico as the ground zero country for 1994 and Thailand for 1997. Van Rijckeghem and Weder (2001) use Russia as the origin of the 1998 crisis. Table 2 shows the countries that are used in each wave.

To quantify the trade channel for contagion we use the "trade share" indicator computed by Glick and Rose (1999) for 1992, 1994 and 1997 and Van Rijckeghem and Weder (2001) for 1998. A high value of this index indicates that the country's exports compete intensely with the ground zero country in third markets.

---

[8] See for example the 1993 World Bank publication "*The East Asian Miracle*" hailing the "fundamentally sound development policies" and "tailored government interventions" in eight high performing Asian economies.
[9] Porter (1996)
[10] See Beck and Levine (2003) for a review
[11] Demirgüç-Kunt and Detragiache. (1998), Kaminsky and Reinhart (1999), Kaminsky and Schmukler (2003)

[12] Glick and Rose (1999) use journalistic and academic histories of crises episodes to identify countries suffering from contagion, Van Rijckeghem and Weder (2001) utilise a panel of IMF experts.

To measure financial links between countries, we choose two indicators of competition for funds based on Caramazza *et al*. (2000). Define the "common lender" to be the creditor country most exposed to the ground zero country. For any given country, our first indicator indexes the importance of the common lender to that country. For the emerging market crises the "common lenders" are the US (1994), Japan (1997) and Germany (1998). For example, in the Russian crisis of 1998 the indicator looks at the proportion of country i's total borrowing which derived from German banks. Our second indicator measures how important a potential target country is to the common lender. Thus, the indicator measures country i's borrowing as a proportion of the total loans made by the common lender. We also include a multiplicative interaction of these two indicators. The data are taken from the Bank for International Settlements' (BIS) consolidated data, covering bank lending from banking systems in the "reporting area" of 18 industrialised countries to countries outside the "reporting area".[13] All indicators refer to banks' position reported at the date closest to the respective crises i.e. December 1994 for the Mexican crisis, June 1997 for the Asian crisis and June 1998 for the Russian crisis. The BIS data only cover lending from the reporting area to countries outside the reporting area, meaning that no financial data are available for the 1992 crisis in the European exchange rate mechanism.[14]

Our analysis of the "wake-up call" hypothesis is based on a number of variables that have been used in the literature to capture institutional similarity between countries. The finance, law and economics literatures have supplied a large set of candidate variables in order to measure institutional quality. While we would like to use as many of those as possible, in order to maximize the size of the sample and reduce multicollinearity problems we ended up with a choice of 6 variables. We use 3 variables taken from the set of governance indicators compiled by Kaufman *et al*. (2003) for the World Bank and another 3 variables from La Porta *et al*. (1998). In particular, the 3 variables from Kaufman et al. (2003) are: corruption, regulatory quality, and the degree to which the rule of law is upheld. The 3 variables from La Porta *et al*. (1998) are government intervention in the banking sector in 1997, business regulation index in

---

[13] The reporting area countries are: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Spain, Sweden, Switzerland, UK and the US.

[14] In any case contagion through a common lender is an unlikely explanation for the crisis in the European Exchange rate mechanism, which was not driven by concerns about the liquidity or solvency of countries' financial sectors or governments, but doubts about the commitment of governments to membership in the system following the asymmetric shock of German Unification. (Buiter *et al*, 1998)

1997 and property rights index in 1999. A disadvantage of these datasets is that data are not available for each of the 4 years we are studying. However, Kaufmann *et al.* (2005) note that the quality of governance tends to be highly persistent, because institutions change only slowly.[15] Changes in governance over time are small relative to the level of the governance indicators and the reported error margin on the estimates. Changes in annual governance estimates where the 90% confidence intervals do not overlap are only reported in a tiny minority of countries.[16] Therefore, in the variables taken from the Kaufman et al. (2003) dataset we take the average score of each country in the years 1996, 1998 and 2000 and used this for each episode of the 1990s currency crises. For each country, and for each relevant variable, we then compute a measure of *similarity* to the ground zero country. For example, let c_i be the corruption index for country i that is constructed as just described, and let c_0 be the same variable measured for the ground zero country. Then the variable that we use in our analysis is defined as: $|c_i - c_0|/|c_o|$. An analogous index of similarity is constructed for the other five institutional variables.

An additional way of capturing institutional similarity derives from legal origin. The large literature on law and finance (e.g. La Porta *et al*. 1998) argues that a country's legal system (mostly acquired through colonisation or occupation) has important effects on how confidently investors transact in a country, and that this differs significantly between Anglo-Saxon common law and French, German and Scandinavian civil law systems.[17] Motivated by this literature, we complement our core measures of institutional similarity summarized above by an indicator of common legal origin, which takes the value 1 if a country has the same legal system as the ground zero country. The data are taken from La Porta *et al*. (1998).

We include relative geographical distance to the ground zero country as a "control variable" in our regressions. Relative distance is relevant as a control for at least two reasons. First, trade competition and financial links tend to be regionally clustered, and thus it is worth considering these effects after controlling for pure geographic regionality. Second, countries that are closer are likely to have more similar institutions and culture. Thus, relative distances may also capture institutional similarity not captured by the more direct measures above. The

[15] http://www.worldbank.org/wbi/governance/pdf/GovMatters_IV_main.pdf
[16] http://www.worldbank.org/wbi/governance/pdf/govmatters3_wber.pdf
[17] See Beck *et al* (2001) for a review

distances between countries were computed as the distances between capital cities, using the distance calculator provided by Darrell Kindred[18] at http://www.indo.com/distance.

Finally, we use a number of macro-economic variables as additional control variables, such as current account and budget deficits, countries' reserve positions, credit expansion, inflation and growth performance. These variables control for the possibility that a country would have fallen into crisis regardless of the attack on the first country, because of its own weak macroeconomic fundamentals.[19] In our choice of control variables, we have been guided by the prior work of Eichengreen *et al*. (1996), Glick and Rose (1999) and Van Rijckeghem and Weder (2003). The variables are computed or taken from the IFS for the period preceding the crisis[20]. This reflects both the delay in data becoming available and the fact that in the immediate aftermath of a currency crisis there is usually a significant worsening of the macroeconomic situation.

4 Methodology

4.1 Bayesian Model Averaging

Let Z be the $n \times k$ matrix that contains all variables that could potentially enter in the regression equation, where n is the number of observations and k is the number of potential regressors. Let $Y = (y_1, ..., y_n)'$ be an $nx1$ vector of observed binary variables. We consider all binary probit models that result from including a different subset of Z as explanatory variables. This gives rise to 2^k models. In particular, model M_j is defined as the following probit model:

$$Y^* \mid \theta \sim N\left(Z_j^{'}\theta_j, I_n\right), \quad y_i = \begin{cases} 1 & if \quad y_i^* \geq 0 \\ 0 & if \quad y_i^* < 0 \end{cases}$$

where $Y^* = (y_1^*, ..., y_n^*)'$ is an $nx1$ vector containing latent data, Z_j is a $n \times k_j$ submatrix of Z, θ is a $k \times 1$ vector of unknown parameters, θ_j is a $k_j \times 1$ subvector of θ containing the elements of θ that are included (i.e., not restricted to be zero) in model M_j, and I_n is the identity matrix of dimension n.

[18] This calculator uses the latitudes and longitudes of the cities concerned and then computes the distance between them by using the Geod program, which is part of the PROJ system, a set of cartographic projection tools, provided by the US Geological Survey at ftp://kai.er.usgs.gov/pub/.

[19] See e.g. Kaminsky *et al* (1998) for a review of the empirical currency crises literature

[20] 1994 for Mexico, 1996 for Asia and 1997 for Russia

Our inference for θ is based on the posterior mean and credible regions[21] of the posterior density of θ ($\pi(\theta \mid Y, Z)$), which is a weighted average of the posterior densities obtained under each of the models ($\pi(\theta \mid Y, Z, M_j)$):

$$\pi(\theta \mid Y, Z) = \sum_{j=1}^{2^k} \pi(M_j \mid Y, Z) \;\; \pi(\theta \mid Y, Z, M_j)$$

Here, $\pi(M_j \mid Y, Z)$ represents the posterior probability of model M_j, which is given by Bayes' Rule as follows:

$$\pi(M_j \mid Y, Z) = \frac{\pi(M_j) \;\; \pi(Y \mid Z, M_j)}{\sum_{l=1}^{2^k} \pi(M_l) \;\; \pi(Y \mid Z, M_l)} \text{ with } \pi(Y \mid Z, M_j) = \int \pi(Y \mid \theta, Z, M_j) \pi(\theta \mid M_j) d\theta$$

and where $\pi(M_j)$ is the prior probability of model j, $\pi(\theta \mid M_j)$ is the prior density of θ under model M_j, and $\pi(Y \mid \theta, Z, M_j)$ is the likelihood.

We now define a crucial concept. The (prior or posterior) *probability of inclusion* for a (possibly singleton) set of explanatory variables S_j is the joint (prior or posterior) probability of all models that include at least one of the variables in S_j. In other words, the probability of inclusion of S_j is the probability that at least one variable in S_j has a non-zero effect on the expected outcome of the dependent variable. Thus, a zero inclusion probability implies that all of the coefficients in θ that correspond to S_j are equal to zero. Inclusion probabilities will be crucial to interpreting our results: variables with high posterior inclusion probabilities are relevant determinants of contagion; others are not.

In the interpretation of results, we will compare the prior with posterior probabilities of inclusion. For this purpose, let the individual prior probability of inclusion of regressor i be denoted as p_i so that the prior inclusion probability of a group of m (h+1,…,h+m) regressors can be calculated as:

$$1 - \prod_{i=h}^{h+m} (1 - p_i)$$

In our empirical analysis we consider two types of priors. In the first type we fix $p_i = \overline{p}$ for every i, where $\overline{p}$ is a fixed value. We call this prior "by Reg.", because it gives each regressor the same prior probability of inclusion. In the BMA literature it is common to follow this

[21] A 95% credible interval is the Bayesian analogue of a frequentist 95% confidence interval, and it is an interval that contains the true value of the parameter with probability 95% (e.g. see Koop 2003, p. 44).

approach with $\overline{p} = 0.5$, which can be seen to imply that all models have equal prior probability[22] (i.e. $\pi(M_j) = \pi(M_i)$ for $i \neq j$). However, in our empirical analysis we want to compare the posterior inclusion probabilities of different groups of regressors. For example, we want to compare the probability of inclusion of trade with that of our 6 institutional variables. The prior "by Reg." biases the results in favour of institutions, because this group contains more variables. For example, if $\overline{p} = 0.5$, the prior inclusion probability of trade is only 0.5, but that of institutions is 0.984. To remedy for this, we also consider a prior in which each regressor, *except for those in the finance group or the institutions group*, has inclusion probability $\overline{p}$. On the other hand, each of the 3 variables in the finance group gets prior inclusion probability equal to $1-(1-\overline{p})^{1/3}$, in such a way that the joint prior inclusion probability of these 3 variables is equal to $\overline{p}$. Similarly, each of the 6 variables in the institutions group gets prior inclusion probability equal to $1-(1-\overline{p})^{1/6}$, in such a way that the joint prior inclusion probability of these 6 variables is again equal to $\overline{p}$. We call this type of prior "By Theory". Along the lines, e.g., of Cremers (2002), as a prior sensitivity analysis, in both the "By reg." and "By Theory" cases, we carry out the analysis with 3 values of $\overline{p}$: 0.15, 0.5 and 0.85.

The Bayesian methodology we use presents two important advantages over its more commonly used classical counterparts in the context of the contagion literature. First, as we have already noted, it allows us to control for model uncertainty. Second, Bayesian methods are valid in small samples. Both of these properties make Bayesian methods particularly suitable for the empirical analysis of financial contagion.

4.2 Prior density for unknown parameters

We use a prior that is computationally convenient and relatively uninformative. For each model M_j, we choose a normal prior as follows:

22 To see this, note that the prior probability of model M_j can be derived from p_i as:

$$\pi(M_j) = \prod_{i=1}^{k} (p_i)^{d_i^j} (1-p_i)^{1-d_i^j}$$

where d_i^j is a binary variable taking value 1 if regressor i enters in model M_j and 0 otherwise. Hence, making p_i=0.5 makes all models equally probable a priori.

$$\theta_j \mid M_j \sim N(0, V), \qquad V_j = g(Z_j^{'} Z_j)^{-1},\ g > 0 \qquad (1)$$

This class of priors has been extensively used for Bayesian estimation (e.g. Zellner, 1986, Poirier, 1985, Fernandez Ley and Steel, 2001). A prior mean of zero implies that we consider outcomes y_i=1 and y_i=0 to be equally likely a priori for i=1,..,n. In addition, it implies that a priori a covariate is as likely to have a positive effect as it is to have a negative effect. The prior variance-covariance matrix depends on the scalar parameter g. It is instructive to think of our choice of g in terms of the implied distribution of the following quantity:

$$\overline{\pi} = \Pr(y = 1 \mid \overline{z}_j, \theta_j, M_j),$$

i.e, the ex ante probability, under model M_j, that the *average* country (a country with average values of regressors) experiences a currency crisis.

While it may be tempting to make our prior "more uninformative" by choosing a very large value of g, it is easy to see that this does not necessarily result in a reasonable prior. Very large values of g imply that, *a priori*, we expect $\overline{\pi}$ to be either 1 or 0 and consequently marginal effects (on probabilities) to be approximately zero.[23] Therefore, instead of arbitrarily fixing a very large value for g, we carefully adapt priors that have been proposed in the existing literature for other related models. In particular, we use three values for g. Details of the prior-elicitation process for g are provided in Appendix A. We summarize our choices here.

Our first choice for g is given by:

$$g = \overline{g} = \left(\overline{z}_j^{'} \left(Z_j^{'} Z_j\right)^{-1} \overline{z}_j\right)^{-1} \qquad (2)$$

This choice is tantamount to assuming that the prior distribution of $\overline{\pi}$ is uniform, a choice recommended by Geisser (1984) for the estimation of a probability.

Our second choice of g is given by

$$g = 2.46\overline{g}$$

This amounts to assuming that the *a priori* distribution of $\overline{\pi}$ is approximately Beta(½,½), a prior recommended in the literature for the estimation of probabilities (Lee 1987). Compared to the

[23] We comment further on this issue in Appendix A.

uniform prior, the Beta prior gives slightly more weight to values of $\bar{\pi}$ near to 0 and 1[24]. Finally, purely for the purpose of sensitivity analysis we also consider $g = 5\bar{g}$. It implies that we give even greater weight to values of $\bar{\pi}$ near to 0 and 1.

We carry out our computations for all three values of g.

4.3 Computation

For our computations, we use the algorithm of Holmes and Held (2006) who extend the methodology of Albert and Chib (1995) to allow for model uncertainty. The Holmes and Held algorithm is a Markov Chain that visits a model (M_n) at each iteration n, and also generates a value for θ conditioning on M_n and the data. Starting with any arbitrary initial model and starting value of θ, Holmes and Held (2006) show that, as the number of iterations increases, the models and parameter values generated can be regarded as a sample from the true posterior distribution of models and parameters. Therefore, posterior means and other quantities of interest can be easily approximated with their sample analogues. The posterior probability of model M_j is given by the proportion of iterations that visit model M_j. We provide details of the algorithm in Appendix A.

5 Results

Our main economic results are presented in Tables 3, 4 and 5[25]. Tables 6 and 7 assess the out-of-sample predictive power of the models. The dependent variable is binary, taking value one if the country concerned suffered a crisis. Since our goal is to understand whether trade competition, financial links, or institutional similarity drive financial contagion, it is important for us to compare the joint probabilities of inclusion of these different categories of variables. For this purpose Table 3 compares the prior and posterior inclusion probabilities for three groups of regressors: finance (*Fi*1, *Fi*2 and *Fi*1**Fi*2), institutional similarity (*Rule of Law*, *Regulatory*

[24] This prior has been found to be the most non-informative according to several criteria (e.g. Jeffreys, 1961, Box and Tiao, 1973, Akaike, 1978 and Bernardo, 1979) in the context of a binomial likelihood. For example, Bernardo (1979) shows that this prior maximizes the expected Kullback-Leibler divergence between the prior and the posterior. In this sense the information in the data is expected to dominate the information in the prior. Because the model with binomial likelihood is the same as a Probit with no regressors but a constant, we informally extrapolate this result to guide our choice of prior.

[25] We iterated the algorithm for 185000 iterations, and discarded the first 5000 iterations. Almost identical results were obtained with an independent run of fewer iterations (65000), indicating good convergence.

Quality, *Corruption, Business Regulation, Bank Intervention.* and *Property Rights.*) and trade. On the other hand, Tables 4 and 5 report three quantities for each regressor. Firstly, we report the prior and posterior probability of inclusion of the regressor (labelled as *pri* and *pos,* respectively), as defined in Section 4.1. This is the probability that the effect associated with a regressor is different from zero. Secondly, since Probit coefficients are hard to interpret, we report the posterior mean for the marginal effect of each regressor. These marginal effects are evaluated at the sample mean of variables.[26] Thirdly, for each marginal effect, we include the 95% credible interval, as defined in Section 4.1. This is the Bayesian analogue to the classical 95% confidence interval in a Maximum Likelihood estimation. Table 3 presents both the "By reg." prior and the "By Theory" prior (as defined in Section 4.1) for several values of $\overline{p}$. Tables 4 – 7 focus on the prior "By Theory" with $\overline{p} = 0.5$. All tables correspond to priors with $g = \overline{g}$ 2.46. The results that we comment upon are robust to prior specifications, unless otherwise stated.[27]

Institutions

The main conclusion from our empirical analysis is that institutional similarity is an important predictor of financial contagion during emerging market crises. As shown in Table 3, in all crises episodes, with the exception of 1992, and for all prior specifications, the joint posterior probability of inclusion of the institutional similarity variables is greater than the prior counterpart. In 1992 the joint prior probability is increased by the data evidence when the prior is "by Theory"[28] but not when it is "by Reg.". In years 1994, 1997 and 1998, credible intervals at 95% for the marginal effects of *Corruption* and *Rule of. Law* always exclude positive values, which is consistent with the wake-up call theory: countries that are institutionally similar to the ground zero country are more likely to experience crises. Among the institutional variables, those with least impact are *Bank Inter*vention and *Business Regulation*., because their prior probabilities of inclusion are never increased by the data evidence in any crisis episode. The

---

[26] Note that since we have a dummy variable among the regressors, namely Legal Origin, by taking the sample mean of variables we are evaluating the marginal effect at the average intercept. The marginal effect for the dummy variable Legal Origin is calculated as the change in probability when Legal Origin changes from 1 to 0. The marginal effects for the finance variables (Fi1 and Fi2) take into account the consequent change in the interaction variable Fi1*Fi2.

[27] Results with the other priors are available from the authors upon request.

[28] Except in the case g=5 and $\overline{p}$ =0.5.

impact of *Property Rights.* is also negligible in all crises except in 1997, where its probability of inclusion increases substantially and its 95% credible interval excludes positive values. By the same standards, the impact of Reg. Q. is important in 1992, 1994 and 1997, but not in 1998.

Since it is difficult to interpret the size of the marginal effects of the institutional similarity variables, we now provide an alternative way of assessing whether the estimated effects are large or small. Consider a country *A* that has the average value for all regressors except for the institutional similarity variables (*Rule of Law*, *Regulatory Quality*, *Corruption, Business Regulation,, Bank Intervention.* and *Property Rights*), all of which take value 0: i.e. the country is identical to the ground zero country with respect to institutions. In addition, consider a country *B* that also has the average value for all regressors, but whose institutional variables take the same value as the country in our sample that is the most dissimilar, in terms of institutions, to the ground zero country[29]. Hence, countries *A* and *B* are different only with respect to institutions. Then, country *A* is affected by the crisis in years 1994, 1997, 1998 with probabilities (11%, 40%, 39%), whereas the corresponding probabilities for country *B* are 0% for both 1994 and 1997 and 1% for 1998.[30] This confirms that institutional similarity played a particularly important role in the direction of spread of the emerging market crises of 1994, 1997 and 1998.

Our results on the effects of common legal origin are less emphatic. The data evidence supports the inclusion of *Legal Origin* only in the crises of 1994 and 1997. In 1997 the 95% confidence interval of *Legal Origin* excludes positive values, indicating that countries with the same legal system as the ground zero country experienced lower probability of crisis. The 1997 ground zero country has British legal origin, which suggests that overall countries with British legal origin were *ceteris paribus* less susceptible to financial crises, which is consistent with the results of the Law and Finance literature.[31] The opposite effect is observed in years 1994 and

[29] The most dissimilar country in our sample is defined as the country that maximises the Euclidean distance with respect to the ground zero country. In terms of the variables that are defined in Section 3 and Table 1, it maximises (R*ule of Law*)^2 + (*Regulatory. Quality*)^2 + (*Corruption*)^2+(*Bank Intervention.*)^2+ (*Business Regulation.*)^2+ (*Property Rights*)^2. According to our data, the most dissimilar countries to the ground zero countries (in terms of institutions) for 1992 (Finland), 1994 (Mexico), 1997 (Thailand) and 1998 (Russia) were Haiti, Singapore, New Zealand and Singapore, respectively.

[30] For 1992 this probability decreases from 3% to zero. These probabilities are calculated assuming that the values of unknown coefficients are equal to the corresponding posterior means for the prior case: "by Theory", $\overline{p} = 0.5$, $g = 2.46\overline{g}$.

[31] See Beck *et al* (2001)

1998, where the ground zero countries have French and (Post-Socialist) civil law legal origins respectively. However, in 1998 the data evidence decreases the prior probability of inclusion.

We now turn to the other potential channels for financial contagion. Our results suggest that, after controlling for institutional similarity, other variables such as financial linkage, trade competition and distance have limited impact. We provide a detailed discussion in what follows.

Finance

Results indicate that finance variables only played an important role in the 1998 crisis. In that year the joint prior probability of inclusion is increased by the data for all prior specifications. In the years 1994 and 1997 the opposite happens for most prior specifications[32]. It can be observed that the marginal effects of $Fi1$ and $Fi2$ in 1998 are positive, since credible intervals exclude negative values. Furthermore, the sizes of the mean marginal effects are non-negligible. Although the effect is not as clear for other years, the evidence for 1998 confirms the intuition that the more dependent the country is on the common lender, the more likely it is that it will be affected by the crisis. A possible interpretation of this result is that contagion through common lenders primarily occurs mainly when lenders are in financial difficulty. The flight to liquidity following the Russian default left many banks exposed and resulted in the near collapse of the hedge fund Long Term Capital Management (LTCM). [33] This led to fears of financial meltdown in mature financial markets.[34] In the other crises international lenders were less compromised in their ability to lend but became more cautious in their lending to certain types of creditors as identified in the "wake-up call" hypothesis.

Trade and Distance

Trade seems to be a very important determinant in the 1994 and 1997 crises, but not in 1992 or 1998. The posterior inclusion probabilities are as high as 94% and 87% in 1994 and 1997, respectively (in the prior specification "by Theory", g= $\bar{g}2.46$ and $\bar{p} = 0.5$). Furthermore, 95% credible intervals in 1994 and 1997 indicate that the possibility of negative values can be

---

[32] Exceptions are: 1994 with $\bar{p} = 0.15$ ("by Reg." and "by Theory") and 1997 also with $\bar{p} = 0.15$ but "by Reg." only.

[33] Kho *et al* (2000) show that banks exposed to LTCM had an abnormal return of – 10.93%, while the equivalent losses suffered by banks exposed to Mexico in 1994 and Korea in 1997 were -1.37% and -1.5%.

[34] "the entire global economic system as we know it almost went into meltdown beginning with Russia's default" Friedman (1999) p 212

confidently neglected, and that mean marginal effects are sizeable, indicating therefore that the trade channel of contagion was probably important in 1994 and 1997. In 1992 and 1998 the posterior inclusion probability of trade is always lower than the prior inclusion probability. The 95% credible interval in 1992 also excludes negative values, suggesting that trade could have played a role in 1992. However, in contrast with Glick and Rose (1999), we find that it is *Distance* that seems to play a more important role in 1992. *Distance* in 1992 is probably simply capturing the fact that EMU countries, which happen to be geographically near, were much more likely to be affected by the crisis.[35] However, the small probability of inclusion of trade in 1992 is not caused by accounting for distance: if we exclude distance from the set of *potential* regressors the probability of inclusion continues to be small. The lack of evidence for contagion to spread along trade lines from Russia in 1998 may reflect that the vast majority of Russian exports were fuel and ferrous and precious metals, where trade is denominated in US$ or (for energy exports to the former Soviet Union countries) is conducted at subsidised prices. Trade partners and competitors may therefore not have been significantly affected by the Russian devaluation.

Out of Sample Predictions

We evaluate the predictive performance of the model using the prior "by Reg." with $\bar{p} = 0.5$ and the following predictive rule, which is defined for γ = 0.5, 0.65, 0.75, 0.9, 0.95:

- y_i is predicted to be one when the posterior mean of $\Pr(y_i = 1|Z) > \gamma$.

- y_i is predicted to be zero when the posterior mean of $\Pr(y_i = 1|Z) < 1- \gamma$.

Predictions are made for (1997, 1998) based on parameter estimates from 1994 data. Similarly, predictions are made for (1994, 1998) based on parameters estimated with 1997 data, and for (1994, 1997) based on 1998 data. For each of these three cases we calculate two error rates: E_0 is the proportion of observations that were predicted to be zero but were actually 1. Similarly, E_1 is

[35] Buiter *et al* (1996) make the important point that the ERM "was the crisis of an exchange rate system rather than the collapse of a collection of unilateral pegs, individually pursued by a number of countries." p4

the proportion of observations that were predicted to be one but were actually 0. Tables 6 and 7 show the results for the case $g=\bar{g}\,2.46$[36].

Table 6 shows that there are very few countries for which the posterior probability of a crisis is high, and this introduces a small sample bias in our estimate of E_1. For example, if 1994 data is used to predict the 1997-98 crises, seven cases have a posterior probability of a crisis greater than 0.95. Five of these actually suffered a crisis: Indonesia in 1997, the Republic of Korea in 1997, Malaysia in 1997, Indonesia in 1998 and Brazil in 1998. The two wrong predicted crises correspond to China in 1997 and in 1998. Therefore the estimated error rate E_1 is 29%, higher than the ideal value of 5%[37]. However, given the small number of cases that are predicted to be 1, the estimate of the error rate is bound to be imprecise.

Predictions and estimates of E_1 were very similar when $g=5\,\bar{g}$. In the case $g=\bar{g}$, however, the number of countries for which y_i is predicted to be one tends to be smaller and the estimated E_1 tends to have more extreme values (e.g. if $\gamma=0.95$, E_1 is zero (i.e. 0/3) when 1994 data is used for calibration, and it is equal to 100% (i.e. 1/1) when calibration data is either 1997 or 1998).

Table 7 shows that E_0 is at most 5% when 1- γ is either 0.05 or 0.1. This suggests that the model produces reliable predictions of zeros, in the sense that a small posterior mean of $\Pr(y_i = 1|Z)$ can be taken as strong evidence against the occurrence of a crisis. The results for the other choices of g are almost identical in this case.

6 Conclusions

We contribute to the empirical literature on financial contagion by considering institutional similarity to the ground-zero country, measured via governance indicators, as a determinant of the direction of spread of currency crises. We find that for the emerging market crises of 1994, 1997, and 1998, institutional similarity played a substantial role in determining the direction of contagion. Simultaneously, we consider more traditional channels of contagion, including trade and financial links. We are thus able to establish the relative importance of these various channels.

---

[36] We also carried out the analysis for the other two choices of g and describe the differences in the following paragraphs.

[37] Note that $\gamma=0.95$ implies that E_1 should be 5%.

Our analysis also utilizes recent econometric methodology that is relevant to the analysis of financial contagion. In the absence of a single unified model of financial contagion, researchers are faced with model uncertainty in estimation and prediction. We use Bayesian model averaging to overcome these problems, a method hitherto unused in the literature on financial contagion.

Our results provide direction to theoretical modellers on the ingredients that should go into a model of financial contagion, particularly with respect to institutions. However, our results suggest that there are important differences between crises. We are therefore still far away from a unified model of financial contagion and accurate prediction of future crises based on past crises.

Bibliography

Akaike, H, (1978), "A new look at the Bayes Procedure," *Biometrika*, 65, 53-59.

Albert, J.H. and Chib, S. (1995), "Bayesian Analysis of Binary and Polychotomous Response Data," *Journal of the American Statistical Association* 88, 669-679.

Allen, F. and Gale, D. (2000), "Financial Contagion," *Journal of Political Economy*, 108, 1-33

Basu R. (1998): Contagion Crises: The Investors' Logic, mimeograph UCLA Los Angeles

Beck, T., Demirgüç-Kunt, A. and Levine, R.E. (2001), "Legal Theories of Financial Development" *Oxford Review of Economic Policy*, 17, 483-501

Beck, T., and Levine, R.E. (2005), "Legal Institutions and Financial Development" in C. Menard and M. Shirley, (eds.), *Handbook of New Institutional Economics*, Kluwer Dordrecht (The Netherlands).

Bernardo, J.M. (1979), "Reference Posterior Distributions for Bayesian Inference" (with discussion), *Journal of the Royal Statistical Society*, B, 41, 113-147.

Box, G.E.P. and Tiao, G.C. (1992), *Bayesian Inference in Statistical Analysis*. Wiley (New York).

Buiter, W.H. & Corsetti, G.M. & Pesenti, P.A., (1996). Interpreting the ERM Crisis: Country Specific and Systemic Issues, CEP Discussion Paper dp0321.

Buiter, W.H. & Corsetti, G.M. & Pesenti, P.A., (1998). "Interpreting the ERM Crisis: Country-Specific and Systemic Issues," Princeton Studies in International Economics 84, International Economics Section, Department of Economics Princeton University,.

Caramazza, F., Luca, A. and Salgado, R. (2000), "Trade and Financial Contagion in Financial Crises," *IMF Working Paper*, WP/00/55.

Cremers, M. (2002), "Stock Return Predictability: A Bayesian Model Selection Perspective," *Review of Financial Studies*, 15, 1223-1249**.**

Dasgupta, A. (2004), "Financial Contagion through Capital Connections: A Model of the Origin and Spread of Bank Panics," *Journal of the European Economic Association*, 2, 1049-1084.

Demirgüç-Kunt, A. and Detragiache, E. (1998), "Financial Liberalisation and Financial Fragility" in *Annual World Bank Conference on Development Economics 1998*, B. Plezkovic and J Stiglitz, (eds.), 303-31.

Drazen, A. (1998), "Political Contagion in Currency Crises," mimeo, University of Maryland.

Dungey, M, Fry, R, González-Hermosillo, B. and Martin, V.L. (2003), "Empirical Modelling of Contagion: A Review of Methodologies," *CERF working paper*, # 8, available at: http://rspas.anu.edu.au/economics/staff/dungey/pdfs/reviewdfgm.pdf

Dungey, M. and Tambakis, D. (2003), "International Financial Contagion: What do we know?" *CERF Working Paper* # 9.

Eichengreen, B, Rose, A. and Wyplosz, C. (1996), "Contagious Currency Crises," *NBER Working Paper* #5681.

Fernández, C, Ley, E. and Steel, M. (2001) "Benchmark priors for Bayesian model averaging," *Journal of Econometrics*, 100, 381-427.

Friedman, T (1999): *The Lexus and the Olive Tree;* Farrar, Strauss Giroux, New York

Geisser, S. (1984) "On prior distributions for binary trials (with discussion)" *American Statistician*, 38, 244-251.

Gerlach, S. and Smets, F. (1995): Contagious Speculative Attacks; *European Journal of Political Economy*, 11, 5-63.

Glick, R. and Rose, A. (1999), "Contagion and Trade: Why Are Currency Crises Regional?" *Journal of International Money and Finance*, 18, 603-617

Goldstein M. (1998): The Asian Financial Crisis; Institute for International Economics Washington DC

Goldstein, I. and Pauzner, A. (2004), "Contagion of Self-Fulfilling Currency Crises Due to the Diversification of Investment Portfolios," *Journal of Economic Theory*, 119, 159-183.

Hernandez, L. and Valdes, R. (2001), "What Drives Contagion: Trade, Neighbourhood or Financial Links?" *IMF Working Paper* WP 01/29.

Holmes, C.C. and Held, L. (2006), "Bayesian Auxiliary Variable Models for Binary and Multinomial Regression," *Bayesian Analysis,* 1, 145-168.

Jeffreys, J. (1961), *Theory of Probability*. Oxford University Press (Oxford).

Kaminsky, G., Lizondo, S. and Reinhart, C. (1998), "Leading Indicators of Currency Crises" *IMF Staff papers*, 45, 1-48.

Kaminsky, G. and Reinhart, C. (1999), "The Twin Crises: the Causes of Banking and Balance of Payments Problems," *American Economic Review* 89, 473-500.

Kaminsky, G. and Reinhart, C. (2000), “On Crises, Contagion and Confusion,” *Journal of International Economics*, 145-168.

Kaminsky, G. and Schmukler, S. (2003), “Short-Run Pain, Long Run Gain: The Effects of Financial Liberalisation” *IMF Working Paper* 2003 / 34.

Kaufmann, D., Kraay, A. and Zoido-Lobaton, P. (2003), “Governance Matters III,” *World Bank Working Paper* # 3106

Kho, B-C., **Lee, D., Stulz**, R. (2000), "US banks, crises, and bailouts: from Mexico to **LTCM**", American Economic Review, Vol. 90 pp.28-31

Koop, G. (2003) *Bayesian Econometrics*. Wiley (London).

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, **R.** (1998), “Law and Finance,” *Journal of Political Economy*, 106, 1113 –1155.

Leamer, E.E., (1978) *Specification Searches: Ad Hoc Inference with Non Experimental Data*, Wiley (New York).

Lee, P. (1987), *Bayesian Statistics: An Introduction*, 1st ed., Oxford University Press (New York).

Pericoli, M. and M. Sbracia, (2003), “A Primer on Financial Contagion,” *Journal of Economic Surveys,* 17, 571-608.

Poirier, D. J. (1985). “Bayesian hypothesis testing in linear models with continuously induced conjugate priors across hypotheses” In *Bayesian Statistics* 2 (J. M. Bernardo, M. H. DeGroot, D. V. Lindley and A. F. M. Smith, eds.) 711–722. North-Holland, Amsterdam.

Porter, M.E. (1996), "Capital Choice: National Systems of Investment," in *As If the Future Mattered: Translating Social and Economic Theory into Human Behavior*, N.A. Goodwin (ed.), Ann Arbor: University of Michigan Press, 15-44.

Rigobon, R. (1998), “Informational Speculative Attacks: Good News is No News," *MIT Working Paper*

Van Rijckeghem, C. and Weder, B.S. (2001). "Sources of Contagion; Finance or Trade?" *Journal of International Economics,* 45, 293-308.

Van Rijckeghem, C. and Weder, B.S. (2003). "Spillovers through banking centers: a panel data analysis of bank flows," *Journal of International Money and Finance*, 22, 483-509.

World Bank: *The East Asian Miracle: Economic Growth and Public Policy*, World Bank Policy Research Report

Zellner, A., (1986), “On assessing prior distributions and Bayesian regression analysis with g-prior distributions”, in: P. Goel and A. Zellner, eds., *Bayesian Inference and Decision Techniques* (North-Holland, Amsterdam).

Table 1: Definition of variables.

Y	Indicator of whether country *i* experienced a currency crisis; Glick and Rose (1999) and Van Rijckeghem and Weder (2001)
Trade	Trade competitiveness as defined in Glick and Rose (1999)
Dom. Cred.	Growth of Domestic Credit
Bud/GDP	Budget Position as a percentage of GDP
CA/GDP	Current account position as a percentage of GDP
Growth	Real rate of GDP per capita growth
M2/Res	Ratio of M2 to central bank foreign reserves
Inflation	Domestic CPI inflation
GDP	GDP per capita at the beginning of the year measured in 1990 US $
Distance	Great circle distance between capitals of country *i* and ground zero country in miles
Legal Origin	Legal Origin Dummy: 1 if a country has the same legal system as the ground zero country
Rule of Law	Similarity, to ground zero country, in the degree to which the rule of law is upheld. Decreasing with similarity. Original data from Kaufmann *et al.* (1999).
Regulatory quality.	Similarity, to ground zero country, in Regulatory quality. Decreasing with similarity. Original data from Kaufmann *et al*. (1999).
Corruption	Similarity, to ground zero country, in Levels of Corruption. Decreasing with similarity. Original data from Kaufmann *et al*. (1999).
Business Regulation	Similarity, to ground zero country, in Business regulation index. Decreasing with similarity. Original data from La Porta *et al*. (1998).
Bank. Intervention	Similarity, to ground zero country, in Government Intervention in the Banking Sector. Decreasing with similarity. Original data from La Porta *et al*. (1998).
Property Rights.	Similarity, to ground zero country, in Property Rights Index. Decreasing with similarity. Original data from La Porta *et al*. (1998).
*Fi*1	The proportion of a country's total borrowing that was borrowed from the common lender.
*Fi*2	A country's borrowing as a proportion of the total loans made by the common lender.
*Fi*1**Fi*2	The product of Fi1 times Fi2.

Table 2: List of Countries.

Countries: A – K					Countries: L - Z				
	1992	1994	1997	1998		1992	1994	1997	1998
Ground Zero	**Finland**	**Mexico**	**Thailand**	**Russia**	Kuwait	n	n	y	y
Argentina	y	Y	y	y	Latvia	n	n	y	y
Australia	y	Y	y	y	Lebanon	n	n	n	y
Austria	y	N	n	n	Lithuania	n	y	y	y
Azerbaijan	n	N	y	y	Madagascar	n	y	y	y
Bahamas	y	Y	n	y	Malaysia	y	y	y	y
Bahrain	y	Y	n	y	Malta	y	y	y	y
Belarus	n	N	y	y	Mexico	y	n	y	y
Belgium	y	N	n	n	Mongolia	n	n	n	y
Bolivia	y	Y	y	y	Morocco	y	y	n	y
Botswana	y	N	y	n	Netherlands	y	n	n	n
Brazil	y	Y	n	y	New Zealand	y	y	y	y
Bulgaria	n	N	y	y	Nicaragua	y	y	y	y
Burkina Faso	n	N	n	y	Nigeria	y	y	n	y
Cameroon	y	Y	n	n	Norway	y	n	n	n
Canada	y	N	n	n	Oman	y	n	n	n
Chile	y	Y	y	y	Pakistan	y	y	y	y
China	n	N	y	y	Panama	y	y	n	y
Colombia	y	Y	y	y	Papua New Guinea	y	n	y	y
Costa Rica	y	Y	y	y	Paraguay	y	n	n	n
Cote d'Ivoire	n	N	n	y	Peru	y	y	y	y
Cyprus	y	Y	y	y	Philippines	y	y	y	y
Czech Republic	n	Y	y	y	Poland	n	y	y	y
Denmark	y	N	n	n	Portugal	y	y	y	n
Dominican Republic	y	Y	y	y	Romania	y	y	y	y
Egypt	y	Y	y	y	Russian Federation	n	y	n	n
El Salvador	y	Y	y	y	Sierra Leone	y	y	n	n
Estonia	n	Y	y	y	Singapore	y	y	n	y
France	y	N	n	n	Slovakia	n	n	y	y
Gabon	y	N	n	n	Slovenia	n	y	y	y
Gambia	y	N	n	n	South Africa	n	y	y	y
Germany, FR	y	N	n	n	Spain	y	n	n	n
Ghana	y	N	n	n	Sri Lanka	y	y	y	y
Greece	y	Y	y	y	Sudan	n	n	n	y
Guatemala	y	Y	y	y	Sweden	y	n	n	n
Guinea	y	N	n	n	Switzerland	y	n	n	n
Guyana	y	N	n	n	Thailand	y	y	n	y
Haiti	y	N	y	y	Trinidad & Tobago	n	y	n	n
Honduras	y	Y	n	y	Tunisia	y	y	y	y
Iceland	y	Y	y	y	Turkey	y	y	y	y
India	y	Y	y	y	Uganda	n	y	y	n
Indonesia	y	Y	y	y	United Kingdom	y	n	n	n
Ireland	y	N	n	n	United States	y	n	n	n
Israel	y	Y	y	y	Uruguay	y	y	y	y
Italy	y	N	n	n	Venezuela	y	y	y	y
Jamaica	n	Y	y	y	Vietnam	n	n	n	y
Japan	y	N	n	n	Yemen, Rep.	n	n	y	y
Jordan	y	Y	y	y	Zimbabwe	n	y	n	n
Kenya	y	Y	y	y					
Korea, Republic	y	Y	y	y					

The character *y* indicates that the country was included in the sample of the corresponding year. '*n*' indicates that it was not. The sample sizes in 1992, 1994, 1997 and 1998 were 71, 56, 54 and 66 observations, respectively.

Table 3: Prior and posterior inclusion probabilities

			By reg			By theory		
		$\bar{p}$	0.15	0.5	0.85	0.15	0.5	0.85
1992	Inst.	Prior	0.623	0.984	1	0.15	0.5	0.85
		Post	0.448	0.929	1	0.162	0.538	0.938
	Trade	Prior	0.15	0.5	0.85	0.15	0.5	0.85
		Post	0.096	0.304	0.562	0.087	0.391	0.746
1994	Finance	Prior	0.386	0.875	0.997	0.15	0.5	0.85
		Post	0.603	0.795	0.987	0.298	0.327	0.614
	Inst.	Prior	0.623	0.984	1	0.15	0.5	0.85
		Post	0.961	0.99	1	0.758	0.71	0.859
	Trade	Prior	0.15	0.5	0.85	0.15	0.5	0.85
		Post	0.496	0.85	0.977	0.737	0.936	0.989
1997	Finance	Prior	0.386	0.875	0.997	0.15	0.5	0.85
		Post	0.622	0.712	0.967	0.077	0.264	0.567
	Inst.	Prior	0.623	0.984	1	0.15	0.5	0.85
		Post	0.926	0.997	1	0.303	0.879	0.971
	Trade	Prior	0.15	0.5	0.85	0.15	0.5	0.85
		Post	0.27	0.589	0.856	0.692	0.873	0.979
1998	Finance	Prior	0.386	0.875	0.997	0.15	0.5	0.85
		Post	0.705	0.965	0.992	0.224	0.638	0.92
	Inst.	Prior	0.623	0.984	1	0.15	0.5	0.85
		Post	0.869	0.99	1	0.353	0.58	0.945
	Trade	prior	0.15	0.5	0.85	0.15	0.5	0.85
		post	0.063	0.275	0.893	0.115	0.337	0.899

Prior and posterior inclusion probabilities for Finance (*Fi*1, *Fi*2 and *Fi*1**Fi*2), institutional similarity (*R. Law*, *Reg. Q.*, *Corrupt, Reg. I., Bank Inter.* and *Prop. R.*) and Trade in the six prior specifications defined in Section 4.1 with g value fixed as g= $\bar{g}$ 2.46.

Table 4: Probabilities of inclusion, posterior mean and credible intervals for the crises in 1992 and 1994.

	Crises in 1992					Crises in 1994				
			Mean and 95% credible interval for marginal effects					Mean and 95% credible interval for marginal effects		
	Pri	*Pos*	Lower limit	Mean	Upper limit	*Pri*	*Pos*	Lower limit	Mean	Upper limit
Trade	0.5	0.39	0	1.77E-02	1.08E-01	**0.50**	**0.94**	0	1.78E-01	7.55E-01
Dom. Cred.	0.5	0.28	0	4.03E-05	2.85E-04	0.50	0.25	-5.72E-05	2.91E-06	8.56E-05
Bud/GDP	0.5	0.30	-4.43E-03	-6.18E-04	0	0.50	0.42	0	7.37E-04	4.76E-03
CA/GDP	0.5	0.24	-1.41E-04	2.39E-04	2.07E-03	0.50	0.22	-1.91E-04	5.23E-05	4.08E-04
Growth	0.5	0.21	-2.16E-03	-2.42E-04	9.74E-05	0.50	0.37	0	4.72E-04	3.08E-03
M2/Res	0.5	0.23	0	5.82E-05	5.42E-04	0.50	0.36	-3.82E-04	-6.33E-05	3.34E-06
Inflation	0.5	0.40	-1.87E-03	-2.98E-04	0	0.50	0.24	-1.69E-05	1.19E-05	8.87E-05
In. GDP	0.5	0.20	0	1.07E-07	9.61E-07	0.50	0.34	-3.43E-06	-3.88E-07	3.55E-07
Distance	**0.5**	**0.96**	-4.44E-05	-1.50E-05	-9.91E-08	0.50	0.22	-3.74E-07	1.75E-08	7.78E-07
Legal Origin	0.5	0.11	-1.87E-03	-6.19E-04	0	**0.50**	**0.66**	0	1.93E-02	2.12E-01
Fi1						0.21	0.10	-8.05E-03	-1.39E-03	2.70E-03
Fi2						0.21	0.16	0	1.56E-01	8.92E-01
*Fi1*Fi2*						0.21	0.13			
Rule of Law	**0.109**	**0.34**	-8.88E-02	-1.18E-02	2.74E-03	**0.11**	**0.46**	-3.39E-02	-5.71E-03	0
Regulat. Q.	**0.109**	**0.18**	-7.78E-02	-1.05E-02	0	0.11	0.07	-7.81E-04	-8.91E-04	0
Corruption	0.109	0.05	0	-1.61E-03	0	**0.11**	**0.21**	-1.26E-02	-1.94E-03	0
Bank Interv.	0.109	0.02	0	5.22E-05	0	0.11	0.04	0	-2.86E-04	0
Business reg.	0.109	0.03	0	5.64E-04	0	0.11	0.04	0	-2.74E-04	0
Property. R.	0.109	0.03	0	-4.18E-04	0	0.11	0.03	0	-3.62E-04	0
Constant	0.5	0.06				0.50	0.77			

Pri and *Pos* are the prior and posterior probabilities of inclusion of each variable, respectively. Bold indicates that the posterior probability of inclusion is larger than the prior one. Choice of *g* is $g = \overline{g}$ 2.46

Table 5: Probabilities of inclusion, posterior mean and credible intervals for the crises in 1997 and 1998.]

	Crises in 1997					Crises in 1998				
			Mean and 95% credible interval for marginal effects					Mean and 95% credible interval for marginal effects		
	Pri	*Pos*	Lower limit	Mean	Upper limit	*Pri*	*Pos*	Lower limit	Mean	Upper limit
Trade	**0.50**	**0.87**	0	2.83E-01	8.97E-01	0.50	0.34	-1.87E-02	1.92E-01	1.11E+00
Dom. Cred.	0.50	0.39	-2.90E-03	-4.56E-04	0	0.50	0.13	0	4.14E-04	5.20E-03
Bud/GDP	0.50	0.47	0	4.93E-03	2.61E-02	0.50	0.16	0	2.32E-03	2.21E-02
CA/GDP	0.50	0.25	-4.35E-03	-4.48E-04	3.65E-04	0.50	0.14	0	6.70E-04	7.56E-03
Growth	0.50	0.38	-2.50E-04	4.33E-03	3.00E-02	0.50	0.14	0	2.25E-03	2.28E-02
M2/Res	**0.50**	**0.96**	8.42E-05	7.59E-03	2.32E-02	0.50	0.30	0	6.34E-03	3.44E-02
Inflation	0.50	0.24	-1.62E-03	-1.60E-04	3.34E-04	0.50	0.16	0	5.96E-04	6.67E-03
In. GDP	0.50	0.33	-1.09E-05	-1.49E-06	3.83E-08	0.50	0.24	-2.64E-05	-1.02E-06	1.92E-05
Distance	0.50	0.24	-2.68E-06	-1.93E-07	1.23E-06	0.50	0.28	0	3.67E-06	2.36E-05
Legal Origin.	**0.50**	**0.66**	-2.15E-01	-7.06E-02	0	0.50	0.18	0	3.14E-02	3.93E-01
Fi1	0.21	0.10	-8.58E-02	-9.52E-03	3.19E-02	0.21	0.04	0	2.20E-01	7.56E-01
Fi2	0.21	0.10	-6.08E-02	9.01E-02	6.05E-01	**0.21**	**0.22**	0	5.03E+00	1.27E+01
*Fi1*Fi2*	0.21	0.09				**0.21**	**0.42**			
Rule of Law	**0.11**	**0.20**	-7.78E-02	-1.03E-02	0	0.11	0.08	-1.36E-01	-1.17E-02	0
Regulat. Q.	**0.11**	**0.48**	-1.80E-01	-3.78E-02	0	0.11	0.05	0	6.12E-03	0
Corruption	0.11	0.08	-6.85E-03	-1.60E-03	0	**0.11**	**0.46**	-4.00E-01	-1.27E-01	0
Bank Interv.	0.11	0.02	0	-8.72E-05	0	0.11	0.11	-5.77E-01	-6.10E-02	0
Business reg.	0.11	0.06	0	7.69E-03	1.14E-02	0.11	0.02	0	1.56E-03	0
Property. R.	**0.11**	**0.49**	-6.73E-01	-1.37E-01	0	0.11	0.02	0	-2.79E-03	0
Constant	0.50	0.66				0.50	0.69			

Pri and *Pos* are the prior and posterior probabilities of inclusion of each variable, respectively. Bold indicates that the posterior probability of inclusion is larger than the prior one. Choice of g is $g = \bar{g}$ 2.46

Table 6: Out of Sample Predictions of 1

	γ	0.5	0.65	0.75	0.90	0.95
1994	E_1	0.66	0.66	0.65	0.30	0.29
	NP	71	58	51	10	7
	AN	26	26	26	26	26
1997	E_1	0.65	0.60	0.50	0.67	0.67
	NP	17	10	6	3	3
	AN	23	23	23	23	23
1998	E_1	0.40	0.29	0.20	0.50	1.00
	NP	10	7	5	2	1
	AN	17	17	17	17	17

y_i is predicted to be one when the posterior mean of $\Pr(y_i = 1|Z) > \gamma$. When the models are estimated with 1994 data, predictions are made for (1997, 1998). Similarly, predictions are made for (1994, 1998) based on 1997 data, and for (1994, 1997) based on 1998 data. *NP* is the number of observations predicted to be 1. E_1 is the proportion of *NP* that was actually 0. *AN* is the actual number of ones in the validation sample. Prior is "by Reg." with $\overline{p} = 0.5$ and $g=\overline{g}$ 2.46.

Table 7: Out of Sample Predictions of 0

	1- γ	0.5	0.35	0.25	0.1	0.05
1994	E_0	0.04	0.03	0.04	0.00	0.00
	NP	49	37	26	17	11
	AN	94	94	94	94	94
1997	E_0	0.16	0.15	0.10	0.04	0.00
	NP	105	84	63	26	8
	AN	99	99	99	99	99
1998	E_0	0.11	0.08	0.05	0.05	0.05
	NP	100	92	82	57	41
	AN	93	93	93	93	93

y_i is predicted to be zero when the posterior mean of $\Pr(y_i = 1|Z) < 1- \gamma$. When the models are estimated with 1994 data, predictions are made for (1997, 1998). Similarly, predictions are made for (1994, 1998) based on 1997 data, and for (1994, 1997) based on 1998 data. *NP* is the number of observations predicted to be 0. E_0 is the proportion of *NP* that was actually 1. *AN* is the actual number of zeros in the validation sample. Prior is "by Reg." with $\overline{p} = 0.5$ and $g=\overline{g}$ 2.46.

Appendix A: Details of Bayesian Methodology

A.1: Prior Elicitation for the parameter g.

We comment first on why we do not simply choose a very large value for g. It is easy to see that choosing very high values for g (which results in a very high prior variance) results in priors that put all probability weight on Pr(y=1)=0 or Pr(y=1)=0. For example, suppose that there is only one regressor in the model and no constant term. A sufficiently large prior variance for the slope coefficient implies that the probability that $Z\theta$ is in the interval (-4,4) is approximately zero. Note that in order to predict the outcome of y_i it does not matter in practice if $Z\theta$ is –5 or –250, since both values result in the probability of y_i=1 being approximately equal to zero. Therefore, since a large prior variance effectively rules out that $Z\theta$ lies in (-4,4), the size of the slope coefficient is no longer relevant, and all we would need, should the prior information be true, in order to predict *perfectly* the outcome of y_i, is the sign of the slope coefficient. Thus, because the prior would be so informative, the only relevant information that we would expect from the data would concern the sign of the slope coefficient. A large amount of data would be necessary to change such strong prior beliefs on large probabilities and small marginal effects.

We comment next on the three values of g that we actually choose. Our first choice of prior fixes a value of g such that:

$$Var(\bar{z}_j^{'}\theta_j) = \bar{z}_j V_j \bar{z}_j^{'} = 1$$

where $\bar{z}_j$ is a k_j×1 vector containing the average sample values of Z_j. This implies the following value of g:

$$\bar{g} = \left(\bar{z}_j^{'}\left(Z_j^{'}Z_j\right)^{-1}\bar{z}_j\right)^{-1}$$

To see why this choice is appealing, recall that $\bar{\pi} = \Pr(y=1 \mid \bar{z}_j, \theta_j, M_j) = \Phi\left(\bar{z}_j^{'}\theta_j\right)$, where Φ is the distribution function of a standard normal and therefore $\bar{\pi}$ is the probability of (y=1) for a country with average values for the regressors. If we fix g to be equal to $\bar{g}$, then our prior for $\bar{\pi}$ is a uniform in the interval (0,1). [38][39]

Another popular choice of non-informative prior to estimate a probability is a Beta(1/2,1/2). In the context of a binomial likelihood, this prior is uninformative according to alternative criteria used by different authors (Jeffreys, 1961, Box and Tiao, 1973, Akaike, 1978 and Bernardo, 1979). Compared to

---

[38] To see why, note that using the second fundamental theorem of calculus, the Jacobian from $\bar{\pi}$ to $\tilde{z} = \bar{z}_j^{'}\theta_j$ is the density function of a standard normal evaluated at $\tilde{z}$.

[39] In addition, we note that if Z contains an intercept term, then expression (2) is equal to n. A value of g equal to n has been recommended in the context of model selection in linear models by Fernandez, Ley and Steel (2001).

the uniform prior, the Beta prior gives slightly more weight to values near to zero and near to 1. In our model, this implies that values of θ_j that were further away from zero would receive greater prior weight. Within our framework, we can achieve this greater weight by choosing $g = a\overline{g}$, with a>1. After experimenting with several values for a, we found that a=2.46 results in a prior for $\overline{\pi}$ that approximates well to a Beta (1/2,1/2). This is illustrated in Figure 1, which shows that our prior for $\overline{\pi}$ when a=2.46 is virtually undistinguishable from the Beta prior. Therefore, the second prior that we consider results from fixing $g = 2.46\overline{g}$. Finally, purely for the purpose of sensitivity analysis we also consider prior (1) with $g = 5\overline{g}$. It implies that we give even greater prior weight to probabilities that are near to one and zero.

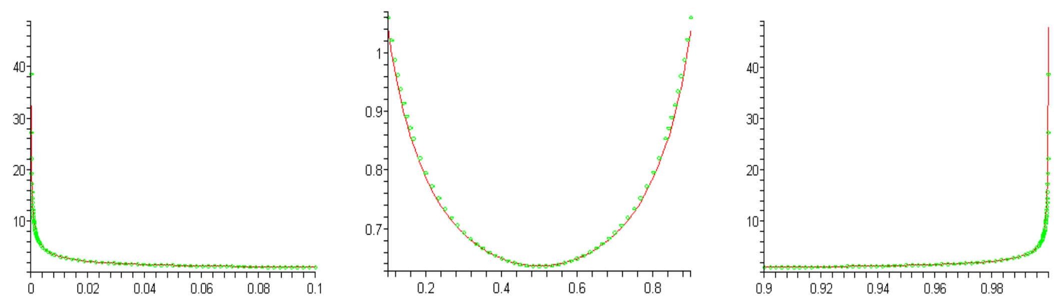

Figure 1: Three views of our prior density for $\overline{\pi}$ with $g = 2.46\overline{g}$ (continuous line) and a Beta(1/2,1/2) (dotted line).

A.2: Computation.

Let M_n be the model visited in the n^{th} iteration of the Markov Chain algorithm, let θ_n be the value of the non-zero parameters in M_n at the n^{th} iteration and similarly let Y_n^* be the value of Y^*. Assuming prior (1) for the parameters in a model, the iteration (n+1) proceeds as follows:

1) Choose a model M^* from a uniform distribution defined on the following set of models:
   - Model M_n
   - Models that result from dropping one regressor in M_n
   - Models that result from adding one regressor to M_n
2) Set M_{n+1} equal to M^* with probability:

$$\alpha = \min\left\{1, \frac{(1+g)^{-k_*/2}\exp\left(-1/2\left(Y_n^*\right)'\left(I_n - 1/(1+g)Z_*V_*Z_*'\right)Y_n^*\right)\pi(M^*)}{(1+g)^{-k_n/2}\exp\left(-1/2\left(Y_n^*\right)'\left(I_n - 1/(1+g)Z_nV_nZ_n'\right)Y_n^*\right)\pi(M_n)}\right\}$$

where I_n is the identity matrix of dimension n, Z_* is a $n \times k_*$ matrix with the set of regressors contained in M^*, k_n is the number of regressors in M_n and V_* and V_n are defined as in (1). Set M_{n+1} equal to M_n with probability 1-α.

3) Draw θ_{n+1} from a normal density with covariance matrix ($\widetilde{V}$) and mean ($\widetilde{\mu}$) equal to:

$$\widetilde{V} = \frac{g}{g+1}\left(Z'_{n+1}Z_{n+1}\right)^{-1} \qquad \widetilde{\mu} = \widetilde{V}Z'_{n+1}Y^*_n$$

where Z_{n+1} is the set of regressors that are included in model M_{n+1}.

4) Draw each of the components of Y^*_{n+1} from univariate truncated normal distributions as explained in Albert and Chib (1995).

We calculate the posterior probability of model M_j as the proportion of iterations that visit model M_j. Similarly, posterior means and credible intervals for θ or functions of θ (e.g. marginal effects) can be calculated using the draws obtained with the algorithm.